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Appendix E1

Quantitative Image Analysis Methods

Figure E1 presents a simplified illustration of the methods used in this study. Density thresholding and region growing were used for preliminary spine segmentation. This preliminary segmentation was then refined by using morphologic operations, with spinal canal extraction performed via watershed algorithm and directed acyclic graph search. Division of disk spaces and vertebrae into separately segmented regions of interest was accomplished by partitioning the spine with three-dimensional vertebral models (1).

While the computer system segmented each thoracolumbar vertebra in its entirety from surrounding structures as part of the initial processing of the axial CT image sets, the algorithm for fracture detection in this preliminary work was designed to limit assessment of fractures to the body portion of the vertebrae to simplify the topological analysis and to focus on the structurally important Denis anterior and middle column injuries in this phase of algorithm design. A novel software algorithm was designed for vertebral body fracture line detection, termed here the *cortical shell unwrapping algorithm* (2). This algorithm segments, or separates, the vertebral body cortex from the underlying medullary space by using deformable dual-surface models to iteratively and precisely detect, fit, and then extract the interior (endosteal) and exterior (periosteal) surfaces of the cortex, forming a "cortical shell" (Fig E1b–E1d). For each vertebral body, a localized cylindrical coordinate system is established as a basis on which each three-dimensional deformable dual-surface cortical shell is then unwrapped (mapped) into a two-dimensional plane (Fig E1e). Fracture lines in the unwrapped cortical shells are detected by means of pattern recognition techniques in which multiscale adaptive filtering methods are used to detect discontinuities in the unwrapped map (Fig E1f).

Fracture line detections in the unwrapped cortical shells are then re-embedded into three-dimensional space, and three-dimensional quantitative features of the fractures relative to the vertebrae are computed. These features can be broadly divided into categories such as comminution complexity, degree of displacement or distraction of the adjacent fragments, spatial morphology, geometric extent of fracture lines, and fracture centroid location. For each three-dimensional fracture detection locus, a set of 28 characteristic features was computed. These features were then submitted to a filter that only allowed detections with features that occurred within preset ranges to pass through. This filtering restricted the number of detections allowed to pass, creating a resultant candidate fracture set. This candidate fracture set was then passed to a detection classifier.

A committee of SVMs was used as the system classifier. The SVM committee was used to categorize detections as positive (fracture) or negative (no fracture), then to compare this SVM categorization with the reference standard data to determine whether there is a TP or FP result (3–7). Each member of the SVM committee had three characteristic features (some of which overlapped between committee members) and was evaluated independently. Training of the SVM committee was performed by using features extracted from detections in the training case data set of CT studies. The labels of the training detections were determined by their overlap with the reference standard data set of fractures manually marked by a radiologist on the same training set. The SVM committee operates by projecting data into high-dimensional feature space, which is divided by a hyperplane into TP and FP regions (3,4,8,9). On the basis of the comparison of the features of the training set, reference standard marked fractures, and features of the detection candidates from computer system analysis, the hyperplane is then optimized for lesion classification. The feature selection was conducted in two stages. A forward stepwise feature selection was first conducted to select the top 1000 three-feature SVMs. Then a second forward stepwise process was performed to select SVMs to form a seven-member committee. An individual score is calculated by each SVM for a given candidate detection, with majority vote determining the committee decision. LibSVM *(http://www.csie.ntu.edu.tw/~cjlin/libsvm/)* was used to establish the individual SVMs. Feature selection and SVM committee formation were developed in-house.

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